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Features Reductions Using Color Moments and Classification of Brain MRI Using K-NN

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Abstract-The paper presents an intelligent method for classification of brain Magnetic Resonance Imaging (MRI). Thep roposed methodology comprises of four stages; pre-processing, feature extraction, feature reduction, and classification. In the first stage, a median filter has been applied on brain MRI to remove the noise and then the image converted to RGB. In the second stage, features of the image have been extracted using Discrete Wavelet Transform (DWT). However, the number of extracted features were very high, which have been reduced in the feature reduction stage using color moments. The feature reduction is the main contribution of this paper. Finally, the reduced features are classified into normal and abnormal MRI using k-Nearest Neighbors (k-NN).The system has proved better results as compared to the other methods with a reduced number of features. The overall accuracy of the proposed method is 94.9745%.

Keywords-Color Moments (CM), Discrete Wavelet Transform (DWT), k-Nearest Neighbors (k-NN), Principal Component Analysis (PCA), Approximation Component.

I. INTRODUCTION

Recognizing brain tumor automatically via magnetic resonance imaging (MRI) is extremely beneficial in treatment designing and neurosurgery. There are different sizes, and characteristics of brain tumors and these elements are essential in the segmentation of anatomical structures. Therefore, due to magnetic field in homogeneity and the intensity variations, it is still a challenging task to detect the size and location of a tumor.

Manual inspection of brain MRI is a tedious task, and it requires expertise. Therefore, the development of an automated analysis tool is necessary for MRI images. To distinguish between normal brain and abnormal brain like stroke, Alzheimer and a brain tumor, the classification of brain MRI is an efficient way. The artificial intelligence-based methods are beneficial in classification and medical image processing. The appropriate use of data mining algorithms can enhance the quality of diagnosis, prediction, and the classification of the disease [i]. Mostly, medical images of the brain are of two types; MRI and X-rays. MRI is well-known to differentiate the soft tissue in a surgical environment and clinical environment. There is no use of destructive ionizing radiation which might affect the patient. To find the presence of a tumor radiologists tests MRI images. The diagnosis accuracy of radiologists decreases with the examination of a large volume of MRI. The sensitivity of the human eye becomes low with a massive number of cases. The identification of tiny portions of the affected brain creates difficulties.

Since last few decades, researchers have developed different methods for the automation of MRI images. The most straightforward stage in brain MRI classification is the pre-processing stage for the enhancement of image quality and noise removal. The noise removal plays an essential role in the accuracy of classification. Mostly the mean filter, median filter, Wiener filter are used for the noise removal. The median filter gives precise results for the removal of salt and pepper noise and preserves the edges during sharpening of the edges of the image [ii].

The role of feature extraction is to convert the image into its sets of features. The image contains lots of features, and for classification, the consideration of all features is not possible. The selection of optimum features is a challenging task. For the feature selection researchers have used Discrete Wavelet Transform (DWT), Gabor Feature, Texture Feature, Spectral Mixture Analysis, Principal Component Analysis, minimum noise fraction transform [iii].Alarge number of features needs to be reduced through dimensionality reduction, to focus on essential features only. Currently, researchers have used principal component analysis (PCA), genetic algorithm, independent component analysis, and linear discriminate analysis for the feature reduction [iv]. Majority of the researchers have used PCA to tackle the dimension reduction problem.

Classification of human brain MRI is possible using supervised and unsupervised techniques. Artificial neural network (ANN), k-NN and support vector machine (SVM) are the most renowned supervised classification techniques. While, self-organization feature map (SOFM), K-means, C-means and fuzzy are the un-supervised techniques.

In this study, we have proposed a new methodology for feature reduction based on the first three statistical moments, namely mean, variance and skewness. The proposed method comprised of four stages namely pre-processing, feature extraction, feature reduction, and classification. In the pre-processing, we have used the median filter for noise removal and also converted the grayscale image to color image. In the feature extraction stage, the haar wavelet has been used. In feature reduction, the statistical moments of the color image channels have been calculated. In the last stage, the KNN has been used. The KNN algorithm has been used because it is the simplest classification algorithm.

The rest of the paper is organized as: section II contains the objective of the paper, section III contains a literature review, Section IV contains the proposed methodology. Section V contains experimental results. The discussion is carried out in Section VI, and finally, section VII contains a conclusion.

II. Objective

The brain tumor remains the most critical research topic for a few decades. For the brain tumor detection mostly, computed tomography (CT) scan and MRI images are preferred. Currently, the experts manually examine the MRI images based on their experience, but this process is time-consuming and prone to errors. The decision-making process relies on the expertise of experts. Using the digital image processing techniques and algorithms the classification of images can be automated. It is also noticeable that the computation time and errors may reduce by applying automated techniques. The primary objective of this paper is to propose an automated model using a median filter, Discrete Wavelet Transform (DWT), color moments and k-Nearest Neighbor (k-NN) to enhance the classification of normal and abnormal images. The other main focus of the paper is to reduce the number of features for better accuracy and fast processing time.

III. Related Work

In [v], authors have used k-Nearest Neighbors and multi-cluster features for brain MRI classification. They have used two-dimensional Discrete Wavelet Transform 2-D (DWT) for feature extraction. They have used multi-cluster feature selection, besides, selection of efficient features from primary features. The selected features were classified into normal or abnormal using k-NN, and they have achieved an accuracy of 98.7%.

In paper [vi] authors have presented a technique to differentiate normal brain MRI from pathological MRI. For the extraction of efficient features, they have used first-order statistics. Features were extracted from horizontal (LH) and vertical (HL) directions. For the classification, they have used k-Nearest Neighbor (k-NN), Learning Vector Quantization (LVQ) and Probabilistic Neural Network (PNN). For the improved classification accuracy and efficiency, the three given classifiers were aggregated in Support Vector Machine (SVM). Different types of features and feature extraction techniques have been presented by [vii]. ANN was used for image retrieval and applied on CBIR domain. In [viii] authors have proposed a four-stage system for real-time object recognition and retrieval using the contour information system.

A model for MRI classification containing three stages was presented by [ix]. Two-dimensional wavelet has been used to extract the valuable features from MRI. However, for dimensionality reduction, Spectral Regression Discriminant Analysis (SRDA) technique has been used. In [x] authors have proposed a technique to detect disease using fuzzy and wavelet techniques from different images. Another model for MR brain images classification was proposed by [xi]. Neural Network techniques have been used for classification of normal and abnormal MR brain images. The wavelet transform was utilized for feature extraction. While, for feature reduction, they have used Principal Component Analysis (PCA). They have achieved a classification accuracy of 100% in both test and training images with a computational time of 0.045s.A five different stages model is used to classify genders that are, face detection, noise removal, face alignment, feature representation, and classification [xii]. DWT, PCA, FP-ANN, and k-NN techniques are used to classify MRI [xv]. The classification of FP-ANN is 90% and in k-NN is 99%. In [xvi] a hybrid method has been used to classify MRI. DWT was used for feature extraction, GA to differentiate the features and SVM for classification. A three stages technique has been used such as preprocessing, feature extraction and classification (probabilistic classifier based on logistic function) to classify the brain MRI [xvii]. Hence the overall obtained accuracy was 94%. In paper [xviii] normal and abnormal brain MRI is classified accuracy of the algorithm was 98%.

IV. Proposed Model

The proposed model is based on four different stages; (1) pre-processing stage (2) feature extraction stage (3) feature reduction stage and (4) and finally, classification stage. The techniques that have been used in the proposed model are Color Moments (CM), Discrete Wavelet Transforms (DWT), and k-Nearest Neighbor (k-NN). The stages of the model can be seen in Fig. 1, the detailed description of each step is provided in the subsequent subsections.

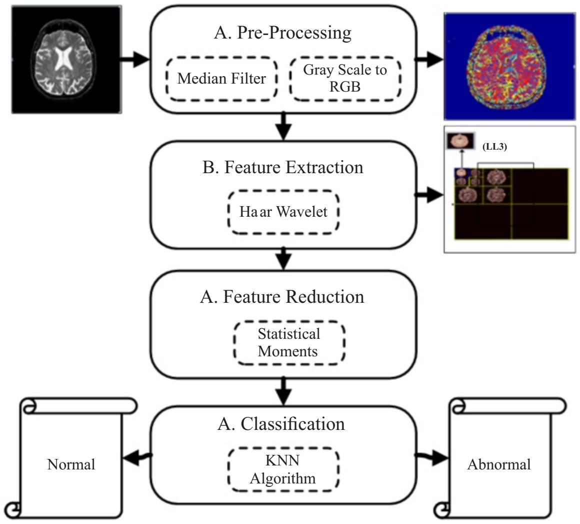
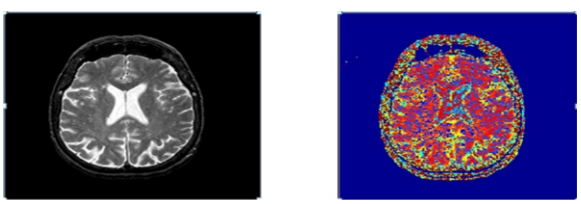


Fig. 1. Proposed Model for Brain MRI Classification

A. Pre-processing

The salt and pepper noise affect MRI images. For the efficient classification results, the brain MRI image must be noise free and sharp. For the removal of the noise, we have used a median filter in the proposed model. For the removal of salt and pepper noise, the median filter works effectively. The median filter preserves the edges and sharpens the image. In the proposed method a 3*3 mask is used because it is a suitable window size. The disadvantage of large size window is, the higher computation time further, it can affect the edges of the image as well [xiii]. After noise removal, the images have been converted to (RGB) images. The RGB image is more informative as compared to the grayscale image as shown in Fig. 2.



a) a Gray-scale image without pre-processing

b) Pre-processed image RGB

Fig. 2. Image without pre-processing and after pre-processing

B. Feature extraction

For the feature, extraction DWT is the most powerful mathematical method. In this paper, DWT has been used for feature extraction from MRI images. The DWT always provide the information of the signal both in the frequency domain and in the time domain. Transforming images from the spatial domain to the frequency domain is the other major advantage of DWT. The basic DWT is given below: Let suppose square-integral function is x (t), then the definition of continues wavelet transform of x (t) related to a given wavelet $\psi_{a,b}(t)$ as:

$$W\psi(a,b)=\int_{-\infty}^{\infty} x(t) * \psi(_{a,b})(t)dx \quad (1)$$

where

$$\Psi_{a,b}(t)= 1/\sqrt{a}\ \psi\ (t\text{-}a/b) \quad (2)$$

In the above equations, the wavelet $\psi_{a,b}$ (t) calculated from mother wavelet ψ (t) by dilation and translation, where 'a' and 'b' represents the dilation and translation parameter respectively, both 'a' and 'b' are considered positive numbers. Wavelets have so many types, in which 'haar' is a frequently used method for image processing because it is the simplest method. Due to DWT, we can decompose an image into sub-bands with DWT relative coefficients.

Through cascading filter banks DWT is implemented in which high pass and low pass filters fulfill specific constraints, as shown in (iii) and (iv).

$$ca_{j,k}(n) = DS[\sum x(n)g^*_j(n\text{-}2^j k)] \quad (3)$$

$$cd_{j,k}(n) = DS[\sum x(n)h^*_j(n\text{-}2^j k)] \quad (4)$$

Here $ca_{j,k}$ denotes the approximate component coefficients, $cd_{j,k}$ refers to the details components coefficients. h(n) shows the high-pass filter and g(n) denotes low-pass filter. k denotes the wavelet transition factor whereas, j denotes wavelet scale factor. DS(↓) operator denotes down sampling. The entire method is known as wavelet decomposition tree, as depicted in Fig. 3.

<table>
<tr><td>3</td><td>HL3</td><td rowspan="2">HL2</td><td rowspan="3">HL1
Vertical detail</td></tr>
<tr><td>LH3</td><td>HH3</td></tr>
<tr><td colspan="2">LH2</td><td>HH2</td></tr>
<tr><td colspan="3">LH1
Horizontal detail</td><td>HH1
Diagonal detail</td></tr>
</table>

Fig. 3. Decomposition tree of a 3-levels

In Fig. 4 we obtained four sub-band (LL, LH, HH, HL) images on every scale by applying the DWT on each dimension separately. LL represents the image approximation component. The rest of the three sub-bands LH, HH, HL represents the components detail about image. The image decomposition can be done by many levels, as we increase the decomposition levels, the complexity of the approximation component becomes higher and higher. The most important thing is, we should remain cautious about the appropriate level of decomposition.

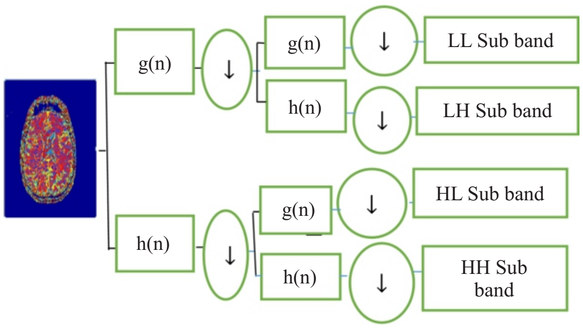


Fig. 4. Schematic diagram of 2D DWT

In the suggested method the decomposition of the image is upto 3 levels we have used haar wavelet for extracting features. The whole subbands layout is illustrated in Fig. 5.The color (RGB) is a transformed image as shown in Fig. 6; the image size is 256*256*3 that is very large for calculation. Therefore, we must compress it without disturbing the information. In the proposed approach, the transformed image was compressed into 3 levels. The decomposition of wavelet upto 3 levels dramatically minimizes the size of the input image as shown in figure 6. The interest of Fig. 6 is the approximate coefficient (LL3) and the total size of same is 32*32*3=3072. However, this size is still large for a classifier, so we have reduced these features further on approximate coefficients at level 3 using color moments.

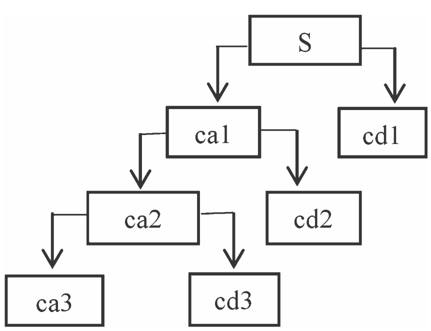


Fig. 5. layout of the wavelet subbands

C. Feature Reduction

For feature reduction we used color moments to reduce the extracted 3072 features, this amount is still very high for classification and also time-consuming. Also, the RGB channels are extracted from each approximate coefficient image at level 3 in the proposed technique. The three-colormoment's standard deviation (variance), mean and skewness are computed for every channel. For classification, these features are too much informative. The mathematical representations of the features are as follows: Equation (v), (vi) and (vii) represents the means, variance, and skewness about the red channel. Equation (viii), (ix) and (x) represents means, variance and as well as skewness of green channel. Equation (xi), (xii) and (xiii) represents the means, variance, and skewness of blue channel.

$$M_{1,1} = \frac{1}{N}\sum_{j=1}^{N} I\, j \quad (5)$$

$$M_{1,2} = \sqrt[2]{\frac{1}{N}\sum_{j=1}^{N}(I_j - M_{1,1})^2} \quad (6)$$

$$M_{1,3} = \frac{1}{N}\sum_{1}^{N}(I_j - M_{1,1})^3 \quad (7)$$

$$M_{2,1} = \frac{1}{N}\sum_{j=1}^{N} I\, j \quad (8)$$

$$M_{2,2} = \sqrt[2]{\frac{1}{N}\sum_{j=1}^{N}(I_j - M_{2,1})^2} \quad (9)$$

$$M_{2,} = \frac{1}{N}\sum_{1}^{N}(I_j - M_{1,1})^3 \quad (10)$$

$$M_{3,1} = \frac{1}{N}\sum_{j=1}^{N} I\, j \quad (11)$$

$$M_{3,2} = \sqrt[2]{\frac{1}{N}\sum_{j=1}^{N}(I_j - M_{3,1})^2} \quad (12)$$

$$M_{3,2} = \sqrt[2]{\frac{1}{N}\sum_{j=1}^{N}(I_j - M_{3,1})^2} \quad (13)$$

Where 'N' depicts the entire quantity of pixels and 'I' depicts each pixel's value intensity.

All the above computations could be summarized as initially, different three color channels such as red, green and blue are acquired from approximate coefficients RGB image at level 3 (LL3 in Fig. 6). After this, we computed the mean, variance and skewness of every channel. We have acquired three color moments for each channel, means we have a total nine features, each channel gets three features. Finally, the features are in a one-dimensional array and then accessed for classification by the k-NN classifier.

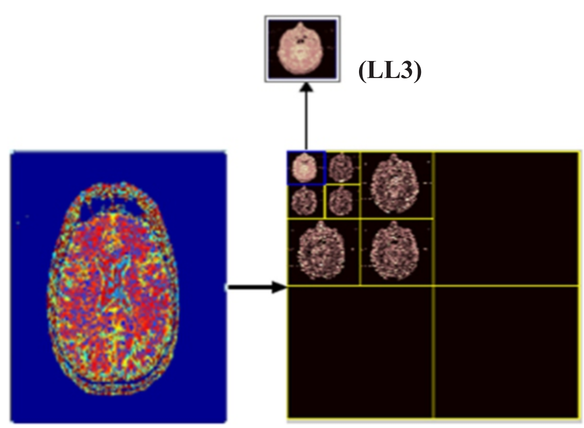


Fig. 6. (RGB) original color image, and its RGB image decomposition upto level 3 and (LL3) is approximate coefficient at level 3

D. Classification

The neural network is a simple classifier where every single pixel is classified in the same class as the training data with the closest intensity. However, there is a possibility of producing a wrong decision in the neural network if the obtained neighbor is an outlier of some other class. Therefore, to overcome these problems and to enhance the robustness of the approach the k-NN classifier works with K patterns. The k-NN classifier is considered as a non parametric classifier because it makes no underlying assumption about the statistical structure of the data [xix]. We have used k-Nearest Neighbors (k-NN) classifier to classify normal and abnormal brain MRI images. Ink-NN, the shortest distance has the likelihood to belong to the same class. E.g., point 'x' probability belongs to a specific class which can be estimated by the proportion of training points in a specified 'x' neighborhood which belongs to that class. The classification of points is dependant on the similarity degree sum method and the majority vote. Mostly, the authors have used the majority voting method as compared to the similarity degree sum method because of its lower sensitivity to outliers. We have used Euclidean Distance in k-NN. The Euclidean distance between each training set point fs and test point ft each having n attributes was calculated using equation (xiv).

$$d = [(f_{t1} - f_{s1})^2 + (f_{t2} - f_{s2})^2 + \dots + \sqrt{(f_{t1} - f_{s1})}] \quad (14)$$

Some of the steps of the k-Nearest Neighbor are summarized as follows:

a) k' selection
b) Distance calculation
c) Sorting distance in ascending order
d) Finding the value of 'k' class
e) Find the dominant class

The optimal 'k' value is a challenging task in the selection, the tiny value for 'k' will not be appropriate for the population proportion to estimate perfectly around the test point. Therefore, the larger value selection of 'k' creates more biased and less variance in estimates probability in the result. So, it is necessary to select 'k' larger to reduce the non-biased decision probability. We have selected the value of 'k' as 3.

V. Implementation and Experimental Results

The selected images of MRI have been taken from www.harvard.edu/AANLIB [xiv].For the experimentation, we have selected 70 standard T-2 weighted brain MRI images, and the size of the images are 256*256. The number of abnormal and normal images are 45 and 25 respectively. The abnormal images contain on these diseases (a) normal brain image (b) brain tumor, (c) stroke and (d) Alzheimer disease as shown in Fig. 7.

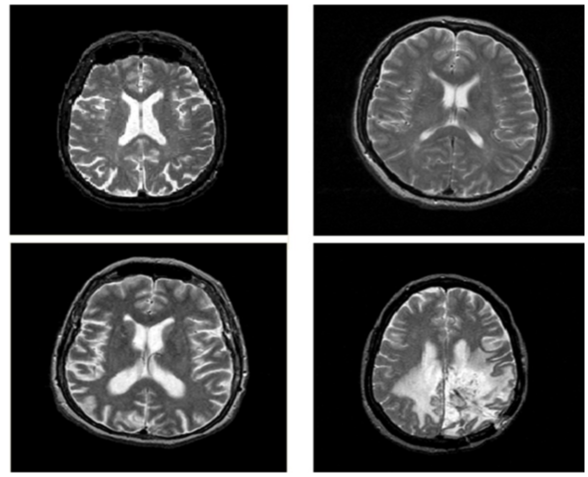


Fig. 7. a) normal brain image b) brain tumor c) stroke d) Alzheimer

A. Experimentation Environment

In this paper, we have used the following software and hardware for the experiments. For pre-processing, feature extraction and feature reduction, we have used Matlab, and weka was used for classification.

Processor: i3-2310M CPU @ 2.10 Ghz
RAM: 8.00 GB
System Type: 64bit
Operating System: Windows 10 Professional
Development Environment: Matlab 7.6.0 (R2008a)
Classification Tool: Weka 3.7.10

B. The ratio of Training and Testing Images

The dataset is divided randomly into two sub-datasets giving 70% ratio to training and 30% to testing. The dataset has total 70 images in which 49 images are for training and 21images are for testing as shown in Table I below. For training dataset, the algorithm accuracy was recorded at 96.6%. While for the testing dataset, the algorithm accuracy was recorded at 93.2%. Hence, the overall accuracy of the algorithm was observed as 94.9%. The proposed method gives some promising results and is good in accuracy and computation. There is one technique which shows better results in accuracy, butits computation is extremely expensive.

The ratio of the division of training testing images is provided in Table I.

TABLE I
RATIO OF TRAINING AND TESTING IMAGES

Total Images		Training Images		Test Images	
70		49		21	
Normal	Abnormal	Normal	Abnormal	Normal	Abnormal
45	25	34	15	15	6

C. Experimental Results

The classification accuracy of normal images using the proposed method is illustrated in Table II. It has been observed that the proposed method gives promising results with the normal images.

TABLE II
TRAINING AND TESTING ACCURACY OF NORMAL IMAGES

Total Images	Correctly Classified	Incorrectly Classified	Accuracy
Training Accuracy of Normal Images			
30	29	1	96.666%
Testing Accuracy of Normal Images			
15	14	1	93.238%

The training and testing accuracy of the abnormal images is shown in Table III. The results show a slight deviation in the accuracy as compared to the normal images.

TABLE III
TRAINING AND TESTING ACCURACY OF ABNORMAL IMAGES

Total Images	Correctly Classified	Incorrectly Classified	Accuracy
Training Accuracy of Abormal Images			
15	15	0	100%
Testing Accuracy of Abormal Images			
10	9	1	90.00%

The comparison of the results with other similar techniques regarding classification accuracy has been carried out in Table IV. The results of the proposed techniques with feature reduction are promising as compared to the other techniques. The reduced features are more accessible to be classified as compared to a large number of features. The computation time also decreases with the feature reduction. The feature-based comparison of the proposed method is carried out in Table V. The proposed technique only utilizes 9 features which are the minimum number as compared to the other techniques. The robustness of the k-NN is that it has provided promising results with just 9 features.

TABLE IV
CLASSIFICATION ACCURACY COMPARISON

Reference No.	Technique	Accuracy Rate
[xiii]	CM+FF-ANN	92.00%
[vi]	DWT+Gabor+SVM	97.36%
[xvi]	DWT+GA+SVM	90.00%
[xv]	DWT+FP-ANN+k-NN	92%
Proposed Technique (with Normal Images)	DWT + Color Features + K-NN (Training)	96.666%
	DWT + Color Features + K-NN (Testing)	93.38%
Proposed Technique (with Abnormal Images)	DWT + Color Features + K-NN (Training)	100.00%
	DWT + Color Features + K-NN (Testing)	90.00%

TABLE V
FEATURE-BASED COMPARISON

Reference No.	Technique	Number of Features
[iv]	DWT + SOM	4761
	DWT + SVM with Linear Kernel	
	DWT + SVM with Polynomial Kernel	
	DWT + SVM with radial basis function based Kernel	
[xi]	DWT+PCA+KSVM	19
Proposed Technique	DWT + CM+ K-NN	9

The proposed model implementation is forthright. We have use DWT for feature extraction from the image. Due to the highness of extracted features, we have used color moments for feature reduction. Most of the researchers do not consider the feature reduction stage. However, this stage is beneficial when the numbers of features are high. In the proposed method we have used total 70 images. It has been noticed during experimentation that with the increase in a number of images the performance of the k-NN decreases. We can say that the performance of k-NN always reduces on more massive data sets. Further, the features reduction is important to step, but during experimentation, it should be minded that the number of features does not decrease to a certain level which might cause the performance decrease or even wrong classification.

VI. CONCLUSION

In this study, developed new method using a median filter, DWT, Color Moments and k-NN to differentiate between normal and abnormal brain MRIs. As we discussed in the literature, different researchers have solved this problem using different techniques in different stages. DWT can effectively extract the desired information from the original image without any loss. Therefore, the extracted features were very high, so we used color moments for feature reduction. In the final stage, k-NN has been used for classification of normal and abnormal brain MRI. The experiments illustrate that the k-NN obtained 96.666% and 93.238% classification accuracy in training and testing data sets with normal images respectively. However, the obtained accuracy of abnormal images is 100.00% and 90.00% during training and testing respectively. The significant contribution of the paper is the reduction in some features as we have carried out experimentation with only 9 features while the other techniques have used a massive amount of features for the classification. The small number of features have reduced the computation time. With the small number of features, we can classify more images using k-NN. Because on more extensive data its performance gets reduces. In human brain how to identify different diseases. For the solution of this issue, a multi-class classification will be beneficial. In future, we will focus on solving this issue as well using multi-class classification.

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